Blowing the Whistle on Opioid Overprescription: Insights from Patient Feedback on Physician Rating Websites

Stanislav Mamonov
Montclair State University
stanislav.mamonov@montclair.edu

Abstract

Overprescription of opioid pain relievers is a known contributor to the growing opioid epidemic. Identification of medical providers that engage in overprescription has proven challenging. We examine the utility of physician rating websites (PRWs) as potential sources of data that may help identify overprescribing practices. We leverage text mining techniques to identify linguistic cues that are associated with known cases of overprescription. We find that patients flag potentially problematic medical providers in their reviews and suggest that intervention by authorities is warranted. Our study contributes to the growing body of literature on medical infoveillance by identifying patients' appeals to regulatory authorities as an important type of social signal for regulatory monitoring.

1. Introduction

The United States is in the middle of an opioid epidemic [39]. The epidemic has its roots in 1990s, when the pharmaceutical companies reassured the medical community that patients would not become addicted to opioid pain relievers and these assurances led to a significant growth in prescriptions [52]. The consequences have been dire. Over 2.1 million people have been diagnosed with an opioid use disorder and more than 47,600 people have died from an opioid overdose [52]. The annual economic burden of the opioid epidemic is estimated at $78.5 billion [50].

Overprescription of opioid pain relievers by some doctors has been noted as a significant contributing factor to the opioid epidemic [9, 34], yet there has been limited action on the part of the state medical boards in reigning in overprescription [24]. This is likely in part due to significant variation in the opioid prescriptions across different types of medical specialties [23], as well as significant variation in the implementation of prescription drug monitoring programs across the individual states [18, 19].

The use of social media as a valuable source of information has been growing across different areas of practice [12, 32]. Patient feedback has been noted as a valuable source of information in improving the quality of healthcare [53]. Given the challenges in using extant data sources in identifying medical providers that may be contributing to the growing opioid problem, we explore the potential value of patient feedback posted on physician rating websites (PRWs) as a source of data in identifying problematic medical providers related to overprescription of opioids. PRWs allow patients to post feedback about their experiences with healthcare providers and PRWs have been growing in popularity among the patients [5, 31].

To evaluate the potential value of patient feedback posted on PRWs, we constructed a dataset of anonymized patient reviews that include known cases of overprescriptions – doctors who had been charged with overprescribing opioids, as well as matched practitioners in the same geographic areas and specialties that, to the best of our knowledge, had not been subject to legal or disciplinary action. Drawing on prior research on text mining in healthcare [33, 49], we applied text mining techniques to explore whether linguistic cues within patient reviews can be a source of information that can help identify overprescription practices. We found that patient feedback posted on PRWs does yield clues to overprescription by specific healthcare providers. We find that patients post appeals to authorities to investigate the healthcare providers that faced legal action at a later date.

Our study makes a contribution to the growing body of medical infoveillance research that focuses on leveraging social media as a source of practically useful insights [51]. Our key theoretical contribution is the identification of whistleblowing as an important type of activity in PRWs that has regulatory implications. Prior research suggested that general social media (Facebook, Twitter, Instagram) can be a useful source of information for pharmaceutical companies in detecting adverse drug side effects [7, 44], as well as for authorities in relation to detecting illicit drug use [42]. Our study shows that PRWs can be a useful source of

URI: https://hdl.handle.net/10125/71094
978-0-9981331-4-0

data in identifying healthcare providers that may be contributing to the opioid overprescription problem.

The remainder of the manuscript is structured as follows. In section 2, we review prior medical infoveillance research as well as prior studies on patient feedback that can be useful in optimizing healthcare practices and outcomes. In section 3, we discuss the methodology in our study. In section 4, we present the results. In section 5, we discuss the results, the contributions of our work to theory and practice, as well as limitations and opportunities for further research.

2. Theoretical and empirical background

The focal research question for our study is whether patient reviews posted on physician rating websites can be a source of information that can help identify medical practitioners that may be engaging in opioid overprescription. The present study falls within the larger domain of medical infoveillance research. Infoveillance is the process of identifying and assessing what is being said about a company, product, brand or individual within forms of electronic interactive media [15]. Infoveillance covers a broad spectrum of potential activities across different domains, e.g. innovation [20] and marketing [14]. In our review of prior research, we specifically focus on medical infoveillance studies. Given that patient reviews constitute the core source of data in our study, we also review prior research on the use of patient feedback in medical care improvement. Because opioid overprescription is an illegal practice [22] that may trigger whistleblowing, we also review research related to whistleblowing.

2.1. Medical infoveillance research

Infoveillance is an emergent area of research that does not yet have a dominant theoretical framework and much of the work on medical infoveillance is exploratory [51]. In reviewing the medical infoveillance research, we examined the focal questions in each study, as well as the unit of analysis and data sources. Table 1 provides a summary of the key studies in this stream of research.

Table 1. Research topics, units of analysis and data sources in medical infoveillance research

Reference / Study focus	Unit of analysis / Data sources	Insights
Caster et al., 2018 [6] Adverse drug side effects	Patients Facebook and Twitter	General social media is a poor source for pharmacovigilance.
Tricco, et al., 2018) [51] Adverse drug side effects	Patients Facebook and Twitter	A review of 46 studies focusing on drug side effects concluded that most of the studies failed to report reliability and validity metrics in the reported analysis.
Anderson et al., 2017 [3] Non-medical use and misuse of bupropion.	Patients Medical forums	Content analysis of postings reveals motivations and methods associated with non-approved drug use.
Cherian, et al., 2018 [8] Drug use portrayal in social media	Social media users Instagram	An exploratory study illustrates normalization of illicit drug use through integration with popular culture.
Chan et al., 2015 [7] Adverse drug side effects	Patients Twitter	It is possible to identify adverse side effects using a sentiment model with Twitter data.
Kim et al., 2017 [27] Opioid misuse	Social media users Twitter	An exploratory analysis shows that 20% of retweeted messages referred to opioid misuse.
Powell, et al., 2016 [44] Adverse drug side effects	Patients Facebook and Twitter	An analysis of 2 years of FB and Twitter data suggests that social media can be a source of information about adverse side effects.
Baumgartner et al., 2017 [4] Drug use	Social media users Twitter	It is possible to identify communities of recreational and illicit cannabis users from Twitter data.
Fan et al., 2017 [16] Real-time drug use detection	Social media users Twitter	The authors develop a system to detect tweets related to illicit drug use in real-time.

We find that the majority of the studies on medical infoveillance focus on either identification of adverse drug side effects [6, 7, 44] or detecting illicit drug use

[4, 16, 27]. While there is disagreement on whether general social media can be a reliable source of information about adverse drug effects [6, 44], there is a consensus on the usefulness of social media in identifying individuals and communities that engage in prescription drug misuse [3], as well as illicit drug use [4, 16, 27].

Focusing on the data sources that are commonly used across published studies, we find that published research has commonly relied on the analysis of data from general (non-medical) social networking sites (Facebook, Twitter, Instagram). The study by Anderson et al. [3] is an exception – the authors explore the misuse patterns of bupropion, a neurotransmitter reuptake inhibitor, using several forums dedicated to addiction recovery. Anderson et al. [3] suggest that more specialized forms of social media related to medical topics can yield richer insights on specific medical issues.

Cherian et al. [8] show that social media is not just a source of potentially useful data for medical infoveillance, but it is also a medium that shapes public perceptions related to drug use. The authors note that depiction of drug use alongside images of popular culture can lead to the normalization of drug use perceptions.

2.2. The value of patient feedback in improving medical practices

In evaluating prior research focusing on the patient reviews as a source of potentially actionable insights in medical practice, we also examined the focal topic of each study, the unit of analysis and the source of data. Table 2 summarizes the key studies that emerged in our review of the literature in this stream.

Table 2. Research topics, units of analysis and data sources in patient feedback related research

Reference / Study focus	**Unit of analysis / Data sources**	**Insights**
Hickson et al., 2002 [22] Malpractice claims	Doctors Proprietary data, a large medical group in the US	Unsolicited feedback is associated with malpractice claims.
Studdert et al., 2016 [48] Malpractice claims	Doctors National Practitioner Data Bank	1% of physicians account for 32% of paid claims.
Wofford et al., 2004 [53] Patient complaints	Topics within the reviews Proprietary data, a large medical center in the US	An exploratory analysis of patient complaints suggests that they fall into the general groups: perceived availability, disrespect, inadequate information, disagreement about expectations of care, distrust, miscommunication, and misinformation.
Montini et al., 2008 [36] Patient complaints	Topics within the reviews Proprietary data	An exploratory analysis of patient complaints suggests that they fall into one of four categories: unprofessional conduct, 2) poor communication, 3) patient treatment or care, or 4) having to wait for care.
Ranard et al., 2016 [46] Patient complaints	Hospital Yelp	A sentiment model reveals most common types of patient complaints that primarily focus on long wait times.
Cooper, et al., 2017 [10] Hospital readmission	Patients National surgical quality improvement program	Unsolicited patient feedback is positively correlated with readmission.

We find that research in this stream tends to focus on the predictive value of patient reviews in relation to hospital readmission [10], medical malpractice claims [22, 48], as well as more general understanding of the key issues that can trigger patient complaints [36, 53]. Published research documents non-uniform distribution of patient complaints about healthcare providers [48] and a significant positive correlation between the volume of unsolicited patient feedback vis-à-vis the likelihood of malpractice claims [22].

We also find several attempts to develop typologies of patient feedback from proprietary databases [36, 53], as well as social media platforms [46]. The developed typologies afford varied degrees of granularity. For example, Montini et al. [36] suggest that patient complaints can be grouped into four general categories: unprofessional conduct, poor communication, patient treatment or care and having to wait. Wofford et al. [53] suggest a more nuanced classification that includes perceived availability, disrespect, inadequate information, disagreement about expectations of care, distrust, miscommunication, and misinformation.

Focusing on the data sources that have been leveraged in prior research on patient feedback, we find that most of the studies are using non-publicly available datasets [10, 22, 36, 48, 53]. The non-public nature of the data is an impediment to replication and integration of the analyses across different data sources. We find only a single study that examined patient feedback in a social media site (Yelp) [46]. The analysis of hospital reviews posted on Yelp suggests that key topics present in the social media feedback are markedly different from those observed in the proprietary datasets. This result implies that the nature of the medium/platform affects the types of comments that patients may post.

Integrating the insights across the studies, we find ample evidence that patient reviews can be a useful source of information in relation to the positive and negative perceptions related to the patient experience with specific healthcare providers. The patient reviews can also be a warning signal that precedes malpractice claims [22, 48]. However, it is important to note that there may be a context effect, wherein the social media platforms may influence the types of the reviewers that are posted. For example, hospital reviews on Yelp have been found to focus on the general affective experience with the hospital rather than specific details [46].

2.3. Whistleblowing

Opioid overprescription exposes medical practitioners to legal risks [25]. Whistleblowing can draw the attention of authorities to potentially problematic practices. Next, we review literature related to whistleblowing with the goal of understanding the key factors that can influence whistleblowing.

Whistleblowing is defined as a disclosure of illegal, immoral, or illegitimate practices to persons or organizations that may be able to effect action [43]. Whistleblowing is a well-developed area of research in the organizational literature [11, 35]. Whistleblowing can be done by actors who are either internal or external to the organization [43]. Several models of whistleblowing have been proposed. Near and Miceli [37] suggested that the key constructs in understanding whistleblowing as a phenomenon are the whistleblower, the complaint, the recipient of the claim, and the subject of the complaint.

Focusing on the individual whisteblowers, Keenan and McLain [26] proposed a process model that progresses through 1) awareness of wrongdoing, 2) assessment of the seriousness of wrongdoing, 3) motivation to correct the wrongdoing, 4) assessment of personal influence over the situation, 5) search for others who can correct the wrongdoing, 6) assessment of consequences for self and others, and 7) choice of action. The choice of action can be affected by the individual characteristics, as well as by situational factors, and it can involve suppression, procedural reporting through prescribed channels, non-procedural reporting, and correcting of wrongdoing by the person herself [26].

One of the key elements that can impede potential reporting of wrongdoing is the consideration of personal consequences for the whistleblower. Whistleblowers often become pariahs in their professional fields [17]. Whistleblowing is particularly rare in the medical field [47]. Studies on the development of effective organizational structures to promote internal reporting on wrongdoing suggest that establishing an independent third party that can serve as a channel for reporting while preserving the whistleblower's anonymity can be an effective strategy in promoting problem reporting by internal organizational actors [43].

In summary, while much of the research on whistleblowing has focused on the employee whistleblowing within organizational contexts, the extant research establishes the focal constructs, as well as a process model for individual cases of whistleblowing that emphasizes the importance of both the individual and contextual factors in affecting the decision to blow the whistle. Specifically, preservation of the whistleblower's anonymity has been identified as a key consideration that affects whistleblowing [43].

3. Methodology

3.1. Data

To explore the potential value of patient reviews posted on the physician rating websites in detecting medical providers that may be engaged in overprescription of opioids, we constructed a dataset of patient reviews from several leading PRWs [31]. To construct the dataset, we started with a list of physicians who have been charged with overprescribing opioids in the period between September 2011 – April 2019. We identified 104 physicians who had been charged with overprescribing opioids and we collected the reviews for these physicians from vitals.com, ratemds.com, and heathgrades.com by scraping the respective web sites. These PRWs were selected because they have better coverage vis-à-vis other PRWs in terms of the number of reviews posted for each physician.

For each physician who had been charged with overprescribing opioids, we identified a matched case without any known legal history related to overprescription, i.e. a physician located in the same general geographic area, practicing in the same medical specialty and having a closely matching overall rating and number of reviews on the PRWs. Our total dataset contained 5795 reviews across 208 physicians. 104 of whom had been charged with overprescription and 104 matched cases with no known legal history related to overprescription of opioids.

We noted the dates that the legal charges were brought up for each accused practitioner in our dataset and we excluded 416 reviews that were posted on PRWs after the respective dates. This left us with 5379 reviews across the 208 physicians.

3.2. Text mining methodology

To examine whether the reviews in our dataset contained linguistic cues that are associated with known cases of overprescription, we built binary classification models using Python version 3.7 [45], Natural Language Toolkit (NLTK) version 3.4.1 [40] and the scikit-learn package version 0.21 [54].

Building classification models using text data involves transformation of text into a set of features (predictors) and leveraging machine learning algorithms to make predictions about the target variable (outcome) [1]. *Charged with overprescription* (yes/no) is the target variable in our models. The "yes" label was assigned to reviews associated with physicians who faced disciplinary or legal charges in relation to overprescribing opioids.

We carried out a series of text pre-processing steps before engineering linguistic features for our models. First, we excluded all personally identifiable and location related information from all of the reviews. Next, we removed stopwords, i.e. common English language words that appear very frequently, but typically contain little information value in modeling, e.g. *the*, *is*, *are*. In the next step, we lemmatized all the words that appeared in the reviews. Lemmatization involves a morphological analysis of the individual words in the reviews and substitution of related forms with lemmas that capture the semantic meaning of the morphological forms. We relied on the WordNetLemmatizer in NLTK version 3.4.1 to perform the lemmatization [41].

Following the pre-processing steps, we transformed each review into an n-gram representation. We included a combination of uni-, bi-, and tri-grams in our models. We built a series of models, applying different classification techniques: logistic regression (LR), decision tree (DT), support vector machine (SVM), and the naïve Bayes (NB) [1]. LR, DT, SVM and NB models are commonly used in data mining analysis of healthcare-related documents [33, 49]. We found the SVM algorithm performed poorly with our data and we excluded SVM models from further analysis.

3.3. Model performance evaluation

The evaluation of model performance focuses on the model ability to correctly predict whether a particular review is associated with a known case of overprescribing. We performed K-fold (K=5) cross-validation of the models [28]. Cross-validation involves splitting the dataset into K subsets and iteratively using different combinations of K-1 subsets to train the models and the remaining subset to evaluate model performance. With 5-fold cross-validation the data are split into 80% for model training and 20% for model testing each time. Cross-validation provides an estimate of model performance dependence on the partitioning of the data into training and validation subsets.

Model performance is evaluated comparing the model predictions on the validation dataset versus the actual values of the target variable. The evaluation of model performance is done based on the metrics derived from the confusion matrix (Figure 1). We focused on the *recall*, *precision*, *F1* and *AUC* metrics related to overprescription in the evaluation of model performance.

Recall, also known as *sensitivity,* measures the proportion of reviews associated with healthcare providers accused of overprescribing that were identified correctly. For example, recall = 0.82 means that 82% of the reviews that were posted for the physicians who had been charged with overprescribing opioids are identified correctly by the model. *Precision* indicates the proportion of the reviews that were predicted by the model to be associated with healthcare practices that were charged with overprescribing are indeed correct. Precision = 0.51 means that 51% of the reviews that a model predicts are posted for the physicians that have been charged with overprescribing opioids are actually correct. *F1* is a harmonic mean of recall and precision. *AUC* stands for "area under the ROC curve" and it is a general measure of the predictive value of a binary classification model. AUC > 0.5 indicates that a model has predictive value vis-à-vis a naïve model [25].

Model prediction

Actual label		No known charges of overprescription	Charged with overprescription
	No known charges of overprescription	True negative (TN)	False positive (FP)
	Charged with overprescription	False negative (FN)	True positive (TP)

Recall = TP / (TP + FN)
Precision = TP / (TP + FP)
F_1 = 2 x (Precision * Recall)/(Precision + Recall)

Figure 1. Confusion matrix and model metrics

4. Results

We found that the naïve Bayes classifier had the best performance. NB classifier recall was 0.826 and NB classifier precision was 0.51. NB model AUC = 0.633. Table 3 below summarizes model performance across different feature representations of the reviews and machine learning algorithms.

Table 3. Model performance summary

	Naïve Bayes	Decision Tree	Logistic Regression
Unigrams			
Recall	0.822 ± 0.025	0.204 ± 0.033	0.108 ± 0.043
Precision	0.501 ± 0.039	0.601 ± 0.074	0.783 ± 0.099
F1	0.622 ± 0.022	0.304 ± 0.043	0.188 ± 0.067
AUC	0.618 ± 0.025	0.554 ± 0.022	0.542 ± 0.013
Bi-grams			
Recall	0.724 ± 0.009	0.095 ± 0.036	0.349 ± 0.044
Precision	0.528 ± 0.019	0.606 ± 0.094	0.637 ± 0.027
F1	0.611 ± 0.015	0.163 ± 0.055	0.450 ± 0.037
AUC	0.631 ± 0.009	0.524 ± 0.014	0.603 ± 0.015
Trigrams			
Recall	0.477 ± 0.028	0.028 ± 0.019	0.401 ± 0.042
Precision	0.529 ± 0.020	0.625 ± 0.213	0.536 ± 0.035
F1	0.501 ± 0.013	0.043 ± 0.033	0.458 ± 0.028
AUC	0.587 ± 0.009	0.506 ± 0.008	0.577 ± 0.014
Ngrams (1-3)			
Recall	0.826 ± 0.030	0.193 ± 0.036	0.214 ± 0.067
Precision	0.513 ± 0.025	0.600 ± 0.079	0.754 ± 0.015
F1	0.633 ± 0.015	0.292 ± 0.051	0.332 ± 0.086
AUC	0.633 ± 0.014	0.551 ± 0.023	0.582 ± 0.026

In the next step of the analysis, we focused on the identification of the most informative features in the best performing model. We relied on the eli5 package implementation [30] of the permutation feature importance algorithm [2] for identification of the most informative linguistic cues in our dataset.

We found that the presence of “medical board” and “DEA” among other cues within the reviews had a significant effect on the likelihood that a medical provider was charged with overprescribing opioids. Table 4 summarizes other most informative features.

Table 4. Most informative linguistic cues

Keyword(s)	Increase in the likelihood of over-prescription charges
medical board	15.7x
dealer	14.3x
DEA	13.6x
legal	7.8x
criminal	7.7x

Following the identification of the informative linguistic cues, we explored the context in which the specific n-grams appeared. Focusing on the top five linguistic markers, we found the following statements within the reviews (informative n-grams are marked in bold):

“The hospital and **medical board** should not let him see or treat patients at any hospital or medical facility.”

“How he can remain in practice is a disgrace to the **Medical Board**.”

“The state **Medical Board** really needs to take a look at this doctor and bar him from practicing medicine.”

“Nothing more than a legalized drug **dealer**.”

“I wanted a doctor, not a **dealer**.”

"All I can say is **DEA** and DOH should inspect.”

"The **DEA** and AMA needs to review all of his records.”

"I wish the **DEA** would do something about this.”

“I’ll be honest its nothing more then a **legal** pill mill.”

“I think what he is doing is **criminal**.”

5. Discussion

5.1. Discussion of results

The goal of our study was to examine whether physician rating websites can be a useful source of information in detecting opioid overprescription by healthcare providers. To address this question, we constructed a dataset of patient reviews posted on leading PRWs that included physicians who had been charged with opioid overprescription as well as matched cases – reviews for doctors located in the same geographic area and practicing in the same specialty, but without any record of criminal or civil charges related to overprescription.

Following a series of data preprocessing steps, we constructed several binary classification models to examine whether n-grams present in the individual reviews can be informative in relation to the known cases where physicians were charged with opioid overprescription. We found that while all models had predictive value, the naïve Bayes classifier exhibited the best performance. 5-fold cross-validation produced average recall of 0.826 and average precision of 0.51.

Focusing on the linguistic cues (n-grams) that had a positive association with the known cases of opioid overprescription, we found that the presence of "medical board", "dealer", and "DEA" in a review increased the likelihood that the review was associated with a known case of opioid overprescription 15.7x, 14.3x, and 13.6x respectively.

Examining the context of the linguistic cues, we found that the identified cues commonly appear within statements questioning the legality of the medical practices and appeals to authorities to review and possibly revoke license for the specific physicians. For example, we find the following in one of the reviews: "The state Medical Board really needs to take a look at this doctor and bar him from practicing medicine." In summary, we find evidence that suggests that patient reviews posted on physician rating websites can be a source of information about potentially problematic opioid overprescription practices. We find that patients flag perceived illegal activities and post appeals to authorities inviting regulatory intervention to address the perceived problems.

5.2. Theoretical implications

Our study makes a number of contributions to theory. First, the key result of our research is that patients use physician rating websites as a channel to blow the whistle on the perceived illicit activities by physicians. The appeals to the regulatory agencies via social media are a novel type of social signal that has not been discussed in prior research. This form of whistleblowing has important regulatory implications and it also has implications for the design of effective social infoveillance systems.

Our study implicates anonymity as an important consideration in the social infoveillance system design. Prior research on whistleblowing has noted that the development of effective reporting systems requires a delicate balance of encouraging problem reporting while minimizing the risks for the whistleblowers [37, 38]. We examined a sample of 150 reviews that contained positive cues associated with potentially problematic practices and we found that 148 of 150 reviews (98.67%) were posted anonymously.

PRWs are reshaping the power relationship between patients and physicians by establishing an anonymous conduit for patients to flag problematic medical providers. Whereas direct appeals to DEA and medical boards may expose patients to legal action by the doctors [22], PRWs achieve the goal of giving the patients a voice while preserving their anonymity and minimizing the risks associated with blowing the whistle.

Our study also makes a contribution to the field of medical infoveillance research. Whereas much of the previous work on the value of social media data has focused on inference about the social media users themselves [4, 16, 27], our work highlights the value of information shared on social media towards gaining insight on the activities of others. The focus on the effects of social media on others would apply to a broad spectrum of medical topics that have implicated social factors, e.g. medication adherence [13], smoking cessation [13], and addiction recovery [13] among them.

Our results also have implications for research on patient feedback in the improvement of healthcare. While much of the previous work had focused on analyzing patient feedback in direct patient communications with the healthcare providers [22, 36, 53], our results reveal that specialized (medical) social media can be an effective tool for detecting problematic medical practices before they undermine the legitimacy of the larger healthcare organizations. Our results suggest that anonymous feedback via social media may encourage the types of patient feedback that patients may self-sensor in direct feedback solicitation by healthcare providers. None of the prior studies that examined direct patient feedback identified appeals to authorities as a type of patient feedback [22, 36, 53].

Finally, our study contributes to the emergent body of research focusing on the reasons that motivate patients to use PRWs [21, 29]. Prior work that examined the role of the pleasure motive vis-à-vis cognitive and executional costs, concluded that these factors provided an incomplete view of the motivations underlying patients' postings on PRWs [21]. Our results indicate that at least some of the reviews are motivated by the need to affect medical practices that are perceived as illegal.

5.3. Implications for practice

The key practical implication of our work is that PRWs may be a useful tool for regulatory medical infoveillance, i.e. it may be possible for the medical boards and other regulatory agencies to develop early warning systems that would capture social feedback across PRWs and help the agencies prioritize the focus of investigative action. The potential for the PRWs to serve as a source of social input for regulatory agencies must be moderated against the potential for false claims. False claims, i.e. unfounded accusations against medical practitioners, can undermine not just the effectiveness of PRWs, but also the effectiveness of the regulatory effort if PRWs become plagued with fake accusations.

5.4. Limitations

We need to note that all research has limitations and this study is no exception. While we made an effort to control for potential confounds and biases in our data by excluding reviews that were posted after the legal action against the specific medical providers was announced publicly, we cannot exclude the possibility that at least some of the whistleblowers may have known about impending legal actions before they were publicly announced. We examined the individual reviews for any indicators that may reveal the authors knowledge of the legal action and we found no such indicators, but we cannot definitively exclude such possibility.

We also need to note that although the medical practitioners in our study were charged with opioid overprescription, in many cases court cases were still pending and therefore it is possible that at least some practitioners would ultimately prevail in the legal proceedings. This is an important limitation in the interpretation of the results of our study.

5.5. Opportunities for future research

Our study provides a foundation for a number of additional research questions that can be pursued. First, while prior research on the factors that can affect whistleblowing has identified anonymity as an important consideration in the decision to report wrongdoing [43], this may not be the only factor that is leading the patients to blow the whistle on PRWs. Further research would be needed to understand the factors that may affect whistleblowing in PRWs. Understanding of these factors would help design better channels to facilitate regulatory social media infoveillance.

We have also noticed that PRWs became the medium for patients' discussion on the doctors' practices after indictments in relation to the specific doctors were announced. Although we excluded these discussions from our analysis because they contained target leaks (information about medical providers after the indictments were announced), we noted that a number of patients came to doctors' defense on PRWs following the indictments. It would be important to understand the dynamics of patient involvement with PRWs and the factors that shape the social climate on PRWs that may affect patients' willingness to use these sites to alert the authorities going forward. PRWs may also become targets for fake reviews and it would be important to investigate potential mitigation strategies for fake information posting.

6. Conclusion

In this study, we examined whether the content of patients' feedback posted on physician rating websites contained any clues about medical providers that were found to engage in opioid overprescription before the public announcement of the indictments. Using text mining techniques we found that patients' reviews contain linguistic cues that flagged problematic practices. Examination of the linguistic cues within their context revealed that patients are using PRWs as a channel to blow the whistle on problematic medical practices. Our findings indicate that PRWs can be a useful source of data for regulatory medical infoveillance.

References

[1] Aggarwal, C.C., and C. Zhai, *Mining text data*, Springer, 2012.

[2] Altmann, A., L. Toloşi, O. Sander, and T. Lengauer, "Permutation importance: a corrected feature importance measure", *Bioinformatics 26*(10), 2010, pp. 1340–1347.

[3] Anderson, L., H.G. Bell, M. Gilbert, et al., "Using Social Listening Data to Monitor Misuse and Nonmedical Use of Bupropion: A Content Analysis", *JMIR Public Health and Surveillance 3*(1), 2017, pp. e6.

[4] Baumgartner, P., and N. Peiper, "Utilizing Big Data and Twitter to Discover Emergent Online Communities of Cannabis Users", *Substance Abuse: Research and Treatment 11*, 2017.

[5] Burkle, C.M., and M.T. Keegan, "Popularity of internet physician rating sites and their apparent influence on patients' choices of physicians", *BMC Health Services Research 15*(1), 2015, pp. 1–7.

[6] Caster, O., J. Dietrich, M. Laure, et al., "Assessment of the Utility of Social Media for Broad - Ranging Statistical Signal Detection in

Pharmacovigilance : Results from the WEB - RADR Project", *Drug Safety 41*(12), 2018, pp. 1355–1369.
[7] Chan, B., A. Lopez, and U. Sarkar, "The canary in the coal mine tweets: Social media reveals public perceptions of non-medical use of opioids", *PLoS ONE 10*(8), 2015, pp. 1–10.
[8] Cherian, R., M. Westbrook, D. Ramo, and U. Sarkar, "Representations of codeine misuse on instagram: Content analysis", *Journal of Medical Internet Research 20*(3), 2018.
[9] Compton, W.M., M. Boyle, and E. Wargo, "Prescription opioid abuse: Problems and responses", *Preventive Medicine 80*, 2015, 5–9.
[10] Cooper, W.O., O. Guillamondegui, O.J. Hines, et al., "Use of unsolicited patient observations to identify surgeons with increased risk for postoperative complications", *JAMA surgery 152*(6), 2017, pp. 522–529.
[11] Culiberg, B., and K.K. Mihelič, "The evolution of whistleblowing studies: A critical review and research agenda", *Journal of Business Ethics 146*(4), 2017, pp. 787–803.
[12] Culnan, M.J., P.J. McHugh, and J.I. Zubillaga, "How large US companies can use Twitter and other social media to gain business value.", *MIS Quarterly Executive 9*(4), 2010.
[13] DiMatteo, M.R., "Social support and patient adherence to medical treatment: a meta-analysis.", *Health psychology 23*(2), 2004, pp. 207.
[14] Dormuth, C.R., T.A. Miller, A. Huang, M.M. Mamdani, and D.N. Juurlink, "Effect of a centralized prescription network on inappropriate prescriptions for opioid analgesics and benzodiazepines", *Cmaj 184*(16), 2012, pp. E852–E856.
[15] Eysenbach, G., "Infodemiology and infoveillance: framework for an emerging set of public health informatics methods to analyze search, communication and publication behavior on the Internet", *Journal of medical Internet research 11*(1), 2009, pp. e11.
[16] Fan, Y., Y. Zhang, Y. Ye, X. Li, and W. Zheng, "Social media for opioid addiction epidemiology: Automatic detection of opioid addicts from Twitter and case studies", *International Conference on Information and Knowledge Management, Proceedings*, (2017), 1259–1267.
[17] Faunce, T.A., and S. Jefferys, "Whistleblowing and scientific misconduct: Renewing legal and virtue ethics foundations", *Med. & L. 26*, 2007, pp. 567.
[18] Fink, D.S., J.P. Schleimer, A. Sarvet, et al., "Association between prescription drug monitoring programs and nonfatal and fatal drug overdoses: A systematic review", *Annals of Internal Medicine 168*(11), 2018, pp. 783–790.
[19] Finley, E.P., A. Garcia, K. Rosen, D. McGeary, M.J. Pugh, and J.S. Potter, "Evaluating the impact of prescription drug monitoring program implementation: A scoping review", *BMC Health Services Research 17*(1), 2017, pp. 1–8.
[20] Goh, K.-Y., C.-S. Heng, and Z. Lin, "Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content", *Information Systems Research 24*(1), 2013, pp. 88–107.
[21] Haug, M., and H. Gewald, "Why do I rate?- Shedding Light on the Factors Influencing the Participation on Physician Rating Websites", *Proceedings of the 52nd Hawaii International Conference on System Sciences*, (2019).
[22] Hickson, G.B., C.F. Federspiel, J.W. Pichert, C.S. Miller, J. Gauld-Jaeger, and P. Bost, "Patient complaints and malpractice risk", *Jama 287*(22), 2002, pp. 2951–2957.
[23] Hill, M. V, Ã.M.L. Mcmahon, R.S. Stucke, and R.J.B. Jr, "Wide Variation and Excessive Dosage of Opioid Prescriptions for Common General Surgical Procedures", *265*(4), 2017, pp. 709–714.
[24] Hoffmann, D.E., "Can state medical boards adequately respond to reports that physicians are inappropriately prescribing opioids?", *Clinical Pharmacology & Therapeutics 81*(6), 2007, pp. 799–801.
[25] Huang, J., and C.X. Ling, "Using AUC and accuracy in evaluating learning algorithms", *IEEE Transactions on knowledge and Data Engineering 17*(3), 2005, pp. 299–310.
[26] Keenan, J.P., and D.L. McLain, "Whistleblowing: a Conceptualization and Model.", *Academy of Management Proceedings 1992*(1), 2011, pp. 348–352.
[27] Kim, S.J., L.A. Marsch, J.T. Hancock, and A.K. Das, "Scaling Up Research on Drug Abuse and Addiction Through Social Media Big Data", *Journal of medical Internet research 19*(10), 2017, pp. e353.
[28] Kohavi, R., "A study of cross-validation and bootstrap for accuracy estimation and model selection", *IJCAI*, (1995), 1137–1145.
[29] Kordzadeh, N., "An Empirical Examination of Factors Influencing the Intention to Use Physician Rating Websites", *Proceedings of the 52nd Hawaii International Conference on System Sciences*, (2019).
[30] Korobov, M., and K. Lopuhin, "ELI5 Documentation", *ELI5 Documentation*, 2020. https://eli5.readthedocs.io/en/latest/blackbox/permutation_importance.html
[31] Lagu, T., K. Metayer, M. Moran, et al., "Website characteristics and physician reviews on commercial physician-rating websites", *Jama 317*(7), 2017, pp. 766–768.
[32] Luo, X., J. Zhang, and W. Duan, "Social media and firm equity value", *Information Systems Research 24*(1), 2013, pp. 146–163.

[33] Luque, C., J.M. Luna, M. Luque, and S. Ventura, "An advanced review on text mining in medicine", *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 9*(3), 2019, pp. e1302.
[34] Makary, M.A., H.N. Overton, and P. Wang, "Overprescribing is major contributor to opioid crisis", *British Medical Journal*, 2017.
[35] Miceli, M.P., J.P. Near, and T.M. Dworkin, *Whistle-blowing in organizations*, Psychology Press, 2008.
[36] Montini, T., A.A. Noble, and H.T. Stelfox, "Content analysis of patient complaints", *International Journal for Quality in Health Care 20*(6), 2008, pp. 412–420.
[37] Near, J., and M. Miceli, "Organizational dissidence: The case of whistle-blowing", *Journal of Business Ethics 4*(1), 1985, pp. 1–16.
[38] Near, J.P., and M.P. Miceli, "Effective-whistle blowing", *Academy of management review 20*(3), 1995, pp. 679–708.
[39] NIDA, "Opioid Overdose Crisis", *NIDA Website*, 2019. https://www.drugabuse.gov/drugs-abuse/opioids/opioid-overdose-crisis
[40] NLTK, "Natural Language Toolkit", 2019. https://www.nltk.org/
[41] NLTK, "Source code for nltk.stem.wordnet", *NLTK 3.4.1*, 2019. https://www.nltk.org/_modules/nltk/stem/wordnet.html
[42] Phan, N.H., S.A. Chun, and J. Geller, "Enabling Real-Time Drug Abuse Detection in Tweets", (March 2018), 2017.
[43] Pittroff, E., "Whistle-Blowing Systems and Legitimacy Theory: A Study of the Motivation to Implement Whistle-Blowing Systems in German Organizations", *Journal of Business Ethics 124*(3), 2014, pp. 399–412.
[44] Powell, G.E., H.A. Seifert, T. Reblin, et al., "Social Media Listening for Routine Post-Marketing Safety Surveillance", *Drug Safety 39*(5), 2016, pp. 443–454.
[45] Python Software Foundation, "Python 3.7.0", 2019. https://www.python.org/downloads/release/python-370/
[46] Ranard, B.L., R.M. Werner, T. Antanavicius, et al., "Yelp reviews of hospital care can supplement and inform traditional surveys of the patient experience of care", *Health Affairs 35*(4), 2016, pp. 697–705.
[47] Rhodes, R., and J.J. Strain, "Whistleblowing in academic medicine", *Journal of Medical Ethics 30*(1), 2004, pp. 35–39.
[48] Studdert, D.M., M.M. Bismark, M.M. Mello, H. Singh, and M.J. Spittal, "Prevalence and characteristics of physicians prone to malpractice claims", *New England journal of medicine 374*(4), 2016, pp. 354–362.
[49] Sun, W., Z. Cai, Y. Li, F. Liu, S. Fang, and G. Wang, "Data processing and text mining technologies on electronic medical records: a review", *Journal of healthcare engineering 2018*, 2018.
[50] TheOpioidCrisis.org, "The Impact — The Opioid Crisis", 2019. https://www.theopioidcrisis.com/the-impact
[51] Tricco, A.C., W. Zarin, E. Lillie, et al., "Utility of social media and crowd- intelligence data for pharmacovigilance : a scoping review", 2018, pp. 1–14.
[52] US Department of Health and Human Services, "About the Epidemic | HHS.gov", 2019. https://www.hhs.gov/opioids/about-the-epidemic/index.html
[53] Wofford, M.M., J.L. Wofford, J. Bothra, S.B. Kendrick, A. Smith, and P.R. Lichstein, "Patient Complaints about Physician Behaviors: A Qualitative Study", *Academic Medicine 79*(2), 2004, pp. 134–138.
[54] "scikit-learn", 2019. https://scikit-learn.org/stable/